Product Market Threats and Stock Crash Risk

Si Li *
Wilfrid Laurier University

Xintong Zhan
Chinese University of Hong Kong

June 12, 2015

Abstract

This paper examines the effect of product market threats on firms' stock crash risk. Competitive pressure from the product market causes a firm to withhold negative information. When negative information is accumulated to a tipping point, the accumulated information all comes out at a time and leads to an abrupt and large decline in stock price. Using fluidity as the main measure of product market threats, our regressions find that firms facing more threats are more prone to stock crashes. This result is confirmed by an instrumental variable analysis and a difference-in-difference analysis with exogenous shock to market competition.

JEL Classification: G3, G12, G14, D4, L1

Keywords: Market competition; Product market threats; Stock crash risk; Tail risk; Bad news withholding

---

* Si Li (sli@wlu.ca), Financial Services Research Centre, School of Business and Economics, Wilfrid Laurier University, Waterloo, Ontario N2L 3C5, Canada, phone: 1(519)884-0710 ext. 2395; Xintong Zhan (xintong@baf.cuhk.edu.hk), Department of Finance, Faculty of Business Administration, Chinese University of Hong Kong. We thank the Center for International Data at the University of California, Davis, the Hoberg-Phillips Data Library, and Feng Li for providing the data used in the paper. We are grateful to Jie (Jay) Cao, Andrew Karolyi, Sophia Zhengzi Li, Chen Lin, Baolian Wang, and Lu Zhang for their helpful comments. We also thank seminar participants at National Taiwan University, Peking University, University of Regina, Zhejiang University, the 2014 Econometric Society China Meetings, the 22nd Conference on the Theories and Practices of Securities and Financial Markets, and the Seventh Biennial McGill Global Asset Management Conference in 2015 for useful comments. Li acknowledges financial support from the Ira Gluskin Fellowship in Finance and the Social Sciences and Humanities Research Council of Canada.

1. Introduction

Large fluctuations in stock prices, especially large sudden drops in asset prices, are one of the primary interests of investors and regulators. Stock market returns are asymmetrically distributed. The increases in stock prices are often gradual, while large declines in the price often occur over a very short period of time. The largest movements in the stock market are usually decreases, rather than increases (Chen, Hong, and Stein, 2001). These largest movements in the market include but are not limited to the stock market crash in 1929 which led to the Great Depression, stock crashes in 1987 and 1989, the collapse of the dot-com bubble in 2000, and the most recent financial crisis in 2008-2009. Because a collapse in share prices often causes widespread and profound disruption to the financial markets and the overall economy, it is of great interest for academics to model stock crashes. These studies include, for example, Chen, Hong, and Stein (2001), Gennotte and Leland (1990), Hong and Stein (2003), and Huang and Wang (2009), among others. They examine the effects of stock market characteristics (such as trading volumes, previous stock prices, and market liquidity) on crashes.

In addition to the above-mentioned studies, recent literature stresses the importance of crash risk of individual firms. For instance, Bali, Cakici, and Whitelaw (2014) mention that "the tail risk of the individual stock will [also] matter for the tail risk of the underdiversified portfolio." Kelly and Jiang (2014) find that common variation in the tail risk of individual firms has strong predictive power for aggregate market returns. There is also a growing interest in how corporate-level characteristics affect the crash risk of individual firms.[1] Overall, the literature deepens our understanding of tail risk by investigating large, negative, market-adjusted returns on individual stocks. We add to this

[1] Later in this section we will discuss in detail the literature on how firm characteristics affect crash risk.

growing literature by examining an overlooked determinant of individual firms' crash risk: product market competitive threats. In this paper, we examine how the product market threats faced by a firm affect its stock crash risk, which is defined as the likelihood and the degree of large stock price declines in individual firms.

Product market competition could affect individual stock crash risk in several important ways. First, competition may increase a firm's stock crash risk. A firm faced with competitive threats has tendency to withhold news, out of the pressures from both the product market and the capital market. Bad news withholding increases crash risk when bad news is accumulated to a threshold and gets released all at once. Specifically, from the aspect of the product market, the proprietary cost hypothesis states that firms avoid disclosing their private information to the public due to proprietary cost (Darrough, 1993; Verrecchia, 1983). Such proprietary cost arises when competitors make strategic use of the disclosed information to weaken the disclosing firms' competitive positions. Stronger threats from competitors increase the proprietary cost and act as a deterrent to information disclosure. Dedman and Lennox (2009) and Ellis, Fee, and Thomas (2012) provide empirical evidence supporting the proprietary cost hypothesis that market competition reduces information disclosure. Graham, Harvey, and Rajgopal (2005) find that nearly three-fifth of their survey respondents agree or strongly agree that giving away company secrets is an important barrier to information disclosure.

From the aspect of the capital market, competition weakens a firm's market share and increases the likelihood of the firm performing poorly. The firm manager thus has tendency to hide bad information in order to manipulate investors' beliefs, so as to reduce the possibility that poor stock performance causes his compensation package to shrink and/or his job to be terminated (Ball, 2009; Graham, Harvey, and Rajgopal, 2005; Kim, 1999; Kothari, Shu, and Wysocki, 2009; Nagar 1999). For example, Kothari, Shu, and Wysocki (2009) present the evidence that firm managers, due to career concerns, accumulate and withhold bad news up to a certain threshold, but immediately reveal good news to investors. Rogers, Schrand, and Zechman (2014) find that managers in the industries with greater equity incentives are more likely to withhold adverse information.

When managers keep hoarding bad news, negative information will be stockpiled and share price will possibly be artificially inflated. Firms, nevertheless, cannot hide adverse information in the long run. Based on the model in Jin and Myers (2006), managers have an abandonment option of releasing accumulated bad news all at once. The option is exercised if the manager is forced to absorb a sufficiently long period of firm-specific bad news and cannot absorb any additional news. When negative firm-specific information is accumulated to a point that exceeds a threshold, the accumulated bad news all comes out at a time and leads to an abrupt and large decline in stock price.[2] According to Kothari, Shu, and Wysocki (2009), the threshold exists because there is a certain point at which it becomes too costly or difficult for managers to withhold bad news. In all, our "information concealing" hypothesis suggests a positive link between market competition and crash risk.

In contrast, competitive pressures from product market may decrease crash risk. There could be two reasons for this. First, competitive threats decrease agency costs and lower agency costs reduce crash risk (Kim, Li, and Zhang, 2011a, b). Threats from competitors force firm managers to run a tight ship: push managers to exert more efforts,

---

[2] Note that bad information release may directly lead to stock price decline, but such price decline may not be *large* enough to become stock crash. We differentiate this from the case that bad information is accumulated and concealed and then all comes out at a time and leads to stock crash.

manage the firm in a more cost-effective way, and make more efficient decisions (Hart, 1983; Schmidt, 1997). This results in possibly an improved firm performance, a decreased likelihood of bad information accumulation, and thus a lower possibility that stock price will drop significantly. Second, a firm may act more conservatively upon increased product market threats from rival firms. For example, Hoberg, Phillips, and Prabhala (2014) show that firms reduce payouts and hold more cash under competitive threats. Dhaliwal, Huang, Khurana, and Pereira (2014) show that firms facing product market threats are more conservative in financial reporting, recognizing accounting losses more timely than gains. The financially conservative reaction to competitive threats can provide more financial flexibility to firms, allowing them to better deal with unfavorable situations and react more aggressively to competitive threats when the threats materialize. Firms are thus less likely to experience large stock price declines. Consistent with this idea, Kim and Zhang (2015) show that accounting conservatism is associated with lower stock crash risk. In sum, the "agency" and "financial conservatism" views suggest a negative relation between competition and stock crashes.

We empirically investigate the impact of product market competition on crash risk to shed light on the above competing views. We measure stock crash risk using two variables: the first crash variable, following Hutton, Marcus, and Tehranian (2009) and Kim, Li, and Zhang (2011a,b), is a dummy variable equal to one for a firm-year if the firm has experienced any firm-specific weekly return more than three standard deviations below the mean return over the entire fiscal year. The second crash variable is the negative conditional return skewness, following Chen, Hong, and Stein (2001).

Our main competition measure is *Fluidity*, constructed by Hoberg, Phillips, and Prabhala (2014). *Fluidity* measures similarity between the change in a firm's product space and the aggregate changes in the competitors' products, and is a forward-looking measure of a firm's competitive threats. When *Fluidity* is greater, the firm's products are more similar to its competitors' and thus the competitive threat is greater. We also use the competition measure constructed by Li, Lundholm, and Minnis (2013), which is the number of occurrences of competition-related words per 1,000 total words in the firm's annual financial reports (10-K). Differing from the traditional industry-level competition measures such as the Herfindahl index and industry concentration ratios, the competition measures we use are firm-specific and thus can better capture firm-level effects.

We start our empirical analysis by a Probit regression (with the crash indicator as the dependent variable) and an OLS regression (with negative return skewness as the dependent variable). Our regression results suggest a significant and positive relation between competitive threats and crash risk. We then note that the primary independent variable, competition, could be endogenous. For example, "good" firms are less likely to face product market threats and such firms also have lower crash risk. Unobserved shocks (such as macroeconomic shocks that we cannot fully control for) could affect both product market competition and stock market crash risk. Reverse causality may also be an issue. For instance, firms with better stock performance (and thus lower crash risk) may gain competitive advantages in product markets by obtaining financing at a lower cost. To mitigate the endogeneity concern, we use instrumental variable and natural experiment approaches.

Specifically, we follow Xu (2012) and use import tariff and foreign exchange rate as instrumental variables for the competitive pressure from foreign rivals. Import tariff forms an important entry barrier for foreign rivals and a reduction in tariffs increases competition. Exchange rate (amount of foreign currency in U.S. dollars) is positively correlated with foreign competition pressure, as a higher exchange rate (indicating that U.S. dollars are more valuable) makes the foreign goods cheaper in U.S. dollars and encourages import. We argue that these two instruments are not related to crash risk through channels other than the competition channel. Our IV regression results confirm that increased competition is associated with greater stock crash risk.

We then use large reductions of U.S. import tariff rates as exogenous shocks to foreign competition. Employing annual import tariff data for U.S. manufacturing industries, we identify significant tariff reductions in each three-digit SIC industry during our sample period. These tariff reductions represent exogenous shocks that significantly change the competitive landscape of the related sectors (Fresard, 2010; Valta, 2012). We obtain consistent results from the difference-in-difference analysis based on the exogenous shocks.

Collectively, our three approaches yield results consistent with stronger market competitions being associated with increased stock crash risk. We argue that the association arises from the channel that product market threats induce managers to hoard unfavorable information. We conduct two tests to support this argument. First, we find that upon more severe threats from competitors, management earnings forecasts become more positive and less negative compared to analyst consensus. This suggests that managers may hide bad news by issuing more positive and less negative earnings forecasts. Second, we study the readability of a firm's annual financial reports (10-Ks). Decreased readability in 10-Ks has been documented to be related to adverse news hiding (Li, 2008; Rogers, Schrand, and Zechman, 2014). Our empirical results show that a firm's 10-Ks become more difficult to read given stronger competitive pressure. These results suggest that managers are more likely to hide bad news when facing more threats from their rivals.

Furthermore, our subsample analysis gives additional support to the information concealing argument. Particularly, if bad information withholding is the channel through which competition affects crash risk, we should see that firms with more disadvantaged positions in market competition are more vulnerable to stock crash because such firms have more unfavorable information and/or are more likely to be influenced by bad news. It is thus natural for us to explore the impact of competitive threats on crash risk conditional on firms' competitive positions and financial strengths. Firms with low market share face higher predation risk as any loss in market share could drive them out of operation. Similarly, firms with financial constraints have greater costs of losing investors' confidence and thus greater incentives to hide adverse news. In addition, firms are better able to hide bad news when the information environment is more opaque (Kothari, Shu, and Wysocki, 2009) and thus we expect to see that the impact of product market threats on crash risk is more severe when there is less transparent information. Our subsample analysis confirms that the positive relation between competitive threats and crash risk is more pronounced in firms with weaker market positions, tighter financial constraints, and more opaque information.

Our contributions to the literature are three-fold. First, the paper adds to the stock crash literature by examining the role of competitive threats from a firm's product market. The existing literature on stock crash is mostly focused on the effects of stock market characteristics on crashes (Chen, Hong, and Stein, 2001, Hong and Stein, 2003, Huang and Wang, 2009, among others). There is a growing literature on how firm characteristics affect the crash risk of individual firms. Hutton, Marcus, and Tehranian (2009) and Jin and Myers (2006) examine the effect of information on crash risk and find that information transparency is related to less crash risk at the individual stock level. Kim, Li, and Zhang (2011a) find that tax avoidance facilitates managerial rent extraction and bad news hoarding activities, which lead to stock price crashes when the accumulated hidden bad news crosses a tipping point and comes out all at once. Kim, Li, and Zhang (2011b) argue that managerial option incentives induce managerial opportunism such as hiding bad news, which is related to higher stock crash risk.

Second, we contribute to the literature on product market competition by showing that an adverse consequence of competition could be large stock price declines. The literature on product market competition consists of two views. The first view holds that competition is good: reducing agency costs (Hart, 1983), increasing firm productivity (Syverson, 2011), and encouraging innovation to some extent (Aghion, Bloom, and Blundell, 2005). The opposite view is that competition has adverse effects: facilitating imitation, discouraging innovation when competition is high (Aghion, Bloom, and Blundell, 2005), causing unethical behavior (Shleifer, 2004), and reducing information disclosure (Dedman and Lennox, 2009; Ellis, Fee, and Thomas, 2012). Our paper adds to this literature by showing that another unfavorable effect of market competition is large share price declines.

Third, the literature has examined the mean and the variance effects of market competition on stock returns, and our paper complements this literature by identifying a significant third moment (skewness) effect. Regarding the mean effect, the evidence on the positive impact of competition on firm productivity suggests that competition increases firm profitability and strengthens firm fundamental cash flows (Galdon-Sanchez and Schmitz, Jr., 2002; Syverson, 2011). On the variance effect, Irvine and Pontiff (2009) find that the increase in idiosyncratic volatility over the past 40 years is attributable to the more intense competition over the years. Valta (2012) finds that competition increases cash flow risk and thus default risk, which is reflected in the increased cost of bank debt. Hou and Robinson (2006) find that firms in more competitive industries earn higher returns and they interpret the finding as these firms being more risky and thus investors commanding higher expected returns. Ang, Chen, and Xing (2006) quantify a significant risk premium for investors bearing downside risk, and Chang, Christoffersen, and Jacobs (2013) find a significant market skewness risk premium. Our results of competition being related to higher skewness risk suggest that the higher returns in firms in more competitive industries could be partially attributed to skewness risk premium.

The rest of the paper proceeds as follows. The next section describes the data, variables, and identification strategies. Main results are given in Section 3. Section 4 provides additional analysis. The last section concludes.

2. Variable Measurements and Identification

2.1 Measuring firm-specific crash risk

We use weekly CRSP stock return data to construct annual firm-specific crash risk. Closely following Kim, Li, and Zhang (2011a,b), for each firm-year, we use weekly returns during the 12-month period ending three months after a firm's fiscal year-end to construct the crash risk variables for the fiscal year. The three month lag ensures that the financial data are available to investors and reflected in stock prices when measuring crash risk (Kim, Li, and Zhang, 2011a). For each firm-year, we require at least 26 weekly stock returns. We exclude observations with non-positive book equity, with non-positive total assets, or with fiscal year-end stock prices less than \$1. We also remove utility (4000≤SIC≤4999) and financial (6000≤SIC≤6999) firms.

We follow two steps to compute firm-specific crash risk. First, for each stock, we run the following regression to remove the impact of market returns and obtain firm-specific weekly returns.

$$r_{i,t} = \alpha_i + \beta_{1i} r_{m,t-2} + \beta_{2i} r_{m,t-1} + \beta_{3i} r_{m,t} + \beta_{4i} r_{m,t+1} + \beta_{5i} r_{m,t+2} + \varepsilon_{it} \, , \qquad (1)$$

where $r_{i,t}$ is the return on stock *i* in week *t*, and $r_{m,t}$ is the return on the CRSP value-weighted market index in week *t*. The lead and lag terms for the market index returns are included to remove the impact of nonsynchronous trading (Dimson, 1979). Specifically, for infrequently traded stocks, the prices recorded at the end of a time period represent the outcome of a transaction which occurred earlier in or prior to the period. Dimson (1979) thus includes preceding, synchronous, and subsequent market returns to deal with the nonsynchronous trading problem. We calculate firm-specific weekly returns as the log residual return: $W_{i,t} = \ln(1 + \varepsilon_{i,t})$.

The second step uses firm specific weekly returns $W_{i,t}$ to construct two crash variables. The first variable, *Crash*, is equal to one if a firm has one or more crash weeks in a fiscal year, and zero otherwise. We define the crash week as the week in which the firm's weekly return $W_{i,t}$ is 3.2 standard deviations below the mean firm-specific weekly returns over the entire fiscal year for this firm. Following Kim, Li, and Zhang (2011a,b), 3.2 is chosen so that the crash events account for 0.07% of frequency in the normal distribution. That is, if firm-specific returns $W_{i,t}$ are normally distributed, one would expect to observe 0.07% of the sample observations crashing in any week.[3]

Our second crash variable is the negative conditional return skewness, *Ncskew*. Following Chen, Hong, and Stein (2001), we calculate *Ncskew* for a given firm year by taking the negative of the third moment of firm-specific weekly returns for each sample year and then dividing it by the standard deviation of firm specific weekly returns raised to the third power:

$$Ncskew_{is} = -\frac{n(n-1)^{3/2}\sum W_{it}^{3}}{(n-1)(n-2)(\sum W_{it}^{2})^{3/2}} \ , \tag{2}$$

where n is the number of observations on weekly returns during year s. Intuitively, *Ncskew* measures left tail thickness, scaled by the standard deviation of the returns. The scaling allows for comparing stocks with different volatilities. The minus sign in front of the equation allows us to interpret the variable in a natural way that an increase in *Ncskew* corresponds to a stock having a more left-skewed distribution and thus being more prone to crash.

[3] We also measure crash risk using 3.09 standard deviations (as in Hutton, Marcus, and Tehranian, 2009) rather than 3.2. 3.09 standard deviations will generate a crash frequency of 0.1%. We obtain similar results by using this alternative measure.

Using weekly returns to construct the crash variables is a trade-off. As noted in Jin and Myers (2006), using short-horizon returns is an advantage in estimating the moments such as skewness. However, the use of high frequency returns could introduce noise or oddly shaped residual returns. For example, a large, negative, firm-specific return in a particular week might reverse in the next week, and not really be the crash predicted by firm fundamentals. We therefore check our results using daily and monthly returns and find robust results.

2.2 Measuring competition pressure

Our main measure of firm-specific competitive pressure is the *Fluidity* variable developed by Hoberg, Phillips, and Prabhala (2014) and available from the Hoberg-Phillips Data Library. *Fluidity* captures the similarity between a firm's own products and the changes of the products made by competitors in the firm's product market. If a firm's products overlap more with the rivals' dynamic changes in their products (i.e., higher *Fluidity*), then the firm faces more competitive threat. We also construct the ranking of product market fluidity, *r_Fluidity*. In each fiscal year, we obtain the decile rank of the sample firms based on their *Fluidity* levels and scale the ranks to be 0.1, 0.2, …, 1. Then we merge the fluidity data with our crash risk data. By requiring non-missing fluidity and control variables, we are left with a sample of 27,955 unique firm-years, covering 4,759 publicly traded U.S. firms over the period from 1998 to 2009.[4]

In addition to *Fluidity* and its transformation *r_Fluidity*, we use *Pctcomp* and *r_comp* (developed by Li, Lundholm, and Minnis, 2013) as alternative measures of firm-specific competitive pressure. Li, Lundholm, and Minnis (2013) count the number of

[4] The fluidity data is from 1997 to 2008 and is lagged in the regression analysis. As a result, our final sample period is 1998-2009. Also, see Appendix for details on control variables.

references to competition in the firm's 10-K filing and develop two measures to capture the notion that more intense behavior from new and existing rivals diminishes a firm's ability to earn profits. *Pctcomp* is the number of occurrences of competition-related words per 1,000 total words in the 10-K, and reflects management's perceptions of the intensity of the competition they face. According to Li, Lundholm, and Minnis (2013), their competition measures are correlated with existing industry-level measures of competition (such as Herfindahl index), but capture something distinctly new. The *Pctcomp* measure has both across-industry and within-industry variations and is related to the firm's future rates of diminishing marginal returns. We merge the *Pctcomp* data (retrieved from Feng Li's website) with our sample, and obtain 17,285 unique firm-year observations with non-missing *Pctcomp*. We then calculate *r_comp*, the decile-ranked value of *Pctcomp*, based on our sample. *r_comp* is computed each year and scaled to be 0.1, 0.2, …, 1. The original sample with available *Pctcomp* ranges from 1995 to 2009. To be consistent with the fluidity sample, we constrain the final sample to be within 1998-2009.

In the paper, we focus on the above-mentioned competition variables rather than the traditional ones such as the Herfindahl index (HHI) and industry concentration ratios (CR). First, *Fluidity* and *Pctcomp* are firm-level variables and capture firm-specific information which is unavailable in the industry-level measures such as HHI and CR. Second, *Fluidity* and *Pctcomp* are forward-looking and incorporate the dynamic actions of a firm's rivals, while HHI and CR are static and based on historical information on firm market shares (Hoberg, Phillips, and Prabhala, 2014; Li, Lundholm, and Minnis, 2013). Third, *Fluidity* and *Pctcomp* capture competition not only from public firms, but also potentially from private firms. Ali, Klasa, and Yeung (2009) find that failing to consider private firms when calculating market shares will result in poor proxies for the actual industry concentration. Hoberg, Phillips, and Prabhala (2014) show that *Fluidity*, though measuring threats from primarily public firms through 10K, is significantly correlated with the competitive threats from private entrepreneurial firms. *Pctcomp* reflects management's perceptions of the intensity of the competition they face, and thus incorporates competition from many sources such as public and private firms and potential new entrants (Li, Lundholm, and Minnis, 2013).

2.3 Instrumental variables for competition

To alleviate potential endogeneity that unobserved factors may affect both competitive threats and crash risk, we use the instrumental variable (IV) method. Specifically, we follow Xu (2012) and use import tariff and foreign exchange rate (both at industry level) as instrumental variables for the competition variable *Fluidity*. These two IVs satisfy the relevance condition because they are correlated with the endogenous variable: market competition. According to Bernard, Jensen, Redding, and Schott (2007) and Tybout (2003), import tariff forms an important entry barrier for foreign rivals and reduces the pressure from import competition. Exchange rate (dollar amount of foreign currency in U.S. dollars) is positively correlated with foreign competition pressure, as a higher exchange rate makes foreign goods cheaper in U.S. dollars and encourages import (Xu, 2012). In addition, both IVs satisfy the exclusion condition because they are arguably not related to firm-level crash risk through any channels other than the competition channel. Later in Section 3.3 and Table 3, we conduct tests to show that the two IVs indeed satisfy the relevance and exclusion conditions.

To obtain the tariff data, for each 3-digit SIC industry year, we calculate the *ad valorem* tariff rate as the duties collected by the U.S. customs divided by the free-on-board value of imports. The information on the duties and the value of imports is collected from Feenstra (1996), Feenstra, Romalis, and Schott (2002), and Schott (2010), which cover the U.S. manufacturing firms for the years until 2005. We obtain the raw exchange rate data from the International Financial Statistics of the International Monetary Fund (IMF). We then convert the raw rate into the real rate using the exchanging countries' consumer price indices obtained from the IMF. Following Xu (2012), we construct the industry-level (three-digit SIC) foreign exchange rate as the source-weighted average of exchange rates across all exporting countries. The weights are the share of each exporting country in the three-digit SIC industry in 1997. We choose 1997 as the base year as our sample begins in 1998. The weights are fixed over time because according to Xu (2012), most industries have stable import shares by country. Overall, our IV regressions are based on the manufacturing firms over the period of 1998-2005.

2.4 Exogenous shock on competition

To better establish a causal relation between competition pressure and crash risk, we further utilize the exogenous reduction in tariff rates as a natural experiment.[5] The substantial reductions in import tariffs initiated by U.S. authorities over the past thirty years create a setting to mitigate endogeneity issues. Similar to the requirement of the instrumental variables, an ideal natural experiment should satisfy both relevance (correlated with the main independent variable competition) and exclusion (exogenous or

[5] We do not use industry deregulation as a shock on market competition because the literature finds that industry deregulation could be endogenous and is affected by industry performance and other factors (Duso and Roller, 2003).

unrelated to the dependent variable crash risk) conditions. Regarding the relevance condition, the literature show that import tariffs are an important fraction of trade costs (Anderson and van Wincoop, 2004) and the reduction of import tariff lowers trade barriers and intensifies foreign competition (Tybout, 2003). Most of the recent tariff changes occurred under the hospice of international institutions such as the General Agreement on Tariff and Trade (GATT) and more recently the World Trade Organization (WTO). We can reasonably argue that the rules of these international institutions are uncorrelated with domestic firms' stock crash risk and thus justify the exclusion condition.

We use the import data from Feenstra (1996), Feenstra, Romalis, and Schott (2002), and Schott (2010). Because there is a significant change in import coding in 1989, we restrict the sample of exogenous shocks to be after 1989. We also exclude the events after 1998 to remove the impact of the confounding factors on stock skewness during the bubble and crisis periods. For each industry-year, we compute the ad valorem tariff rate as the duties collected by the U.S. customs divided by the free-on-board value of imports. We define a negative shock to import tariffs in year *t* to be one if the tariff reduction is greater than the median reduction in the same industry over the entire sample period. To ensure that the tariff reduction events are non-transitory, we exclude the events followed by large tariff increases within the next two years (Fresard, 2010). We also exclude the events with the ex-ante tariff rates smaller than 1% because import restrictions with such low tariff rates are likely minimal.[6] To make sure that each event is not contaminated by subsequent events, for any significant tariff reduction in industry j in year t, we require no other significant reductions in the years from t+1 to t+3. Overall, our natural experiment

[6] The mean import tariff rate is 1.1% and the standard deviation is 1.9% (see Table 1).

sample contains 3,108 firm-year observations in 1,037 U.S. manufacturing firms over the period of 1991-1997.

We follow Fresard (2010) and classify the events into five categories based on the magnitude of the tariff reduction. Specifically, we code the variable *Cut #x* (with x = 1, 2, 3, 4, and 5) as one if the reduction in the import tariff rate is at least x times the median tariff reduction in the same three-digit SIC industry, and zero otherwise. We then examine the change in the crash risk in these five categories of tariff reductions. As we look at the three-year windows around the natural experiment, we average the *Crash* Dummy and *Ncskew* during the three years before and after the exogenous shock, respectively. The differences of the crash risk before and after the events are the effect of exogenously intensified foreign competition on firms' crash risk.

We also use the extreme reduction, *Cut #5*, in the propensity score matching analysis. After merging with the crash risk data, we are left with 16 *Cut #5* events. Untreated firms are those with import tariff reduction lower than the median tariff cut during the period of t to t+3. The average import tariff rate for all treated firms (those with *Cut #5* being 1) decreases from 2.3% before the tariff cut to 1.7% after (a 25% cut), while the tariff rate for untreated firms decreases from 1.38% to 1.27% (an 8% cut).

3. Empirical Results

3.1 Univariate analysis

Table 1 presents the summary statistics of and the correlations between the variables used in the regression analysis. After deleting the observations with missing control variables, our sample contains 27,995 unique firm-years from 4,759 publicly traded U.S. firms from 1998 to 2009. The summary statistics in Panel A show that all the variables are within reasonable ranges and in line with the statistics reported in the literature (Chen, Hong, and Stein, 2001; Kim, Li, and Zhang, 2011a,b; Hoberg, Phillips, and Prabhala, 2014). 18.4% of the sample observations experience one or more crash weeks during each year. The average *Ncskew* is positive (0.018), indicating that the sample firms' returns are negatively skewed on average. The median *Ncskew* is negative at -0.017 and much lower than the mean value, suggesting that a few firms experience extremely low returns.

[Table 1 here]

In Panel B, we report the correlations of crash risk, competition measures and control variables. The correlation matrix shows that the two crash risk measures are highly correlated, with a correlation of 0.64. Our main competition measure, *Fluidity*, is positively related to both measures of crash risk. The correlation is 0.03 for the *Crash* indicator and 0.05 for *Ncskew*. The other three competition measures are also positively correlated with the crash variables. These correlations suggest that firms facing more competitive threats are also more prone to stock crash. The table further shows that the correlations between the control variables are at reasonable levels and do not present any collinearity problem.

3.2 Evidence from the Probit and OLS regressions

In this section, we run Probit (with the dependent variable being the *Crash* indicator) and OLS (with the dependent variable being *Ncskew*) regressions that link our four measures of competition threats (*Fluidity*, *r_Fluidity*, *Pctcomp*, and *r_comp*) in year *t-1* to firms' crash risk in year *t*. A positive coefficient on the competition variables indicates that competition increases a firm's crash risk. Following the literature on the determinants of crash risk (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a,b), we control for a variety of variables, which are defined in detail in Appendix. The regressions also control for industry fixed effects and year effects.

In Table 2 Panel A, we report the marginal effects of competitive threats (evaluated at mean) on the *Crash* indicator. Consistent with the positive correlations observed in Table 1, all the four competition measures have statistically significant and positive coefficients. We also evaluate the economic significance of the marginal effects. The coefficient on *Fluidity* is 0.066. Given a one standard deviation change (0.2) in *Fluidity*, the probability of *Crash* changes by 0.066×0.2 = 0.0132. This is compared to the average *Crash* of 0.184 and the standard deviation of *Crash* of 0.388. Later we show in Table 3 Column (3) that the instrumental variable regression gives a much larger marginal effect estimate of 0.344, which generates greater economic magnitude of 0.0688 (=0.344×0.2). The coefficients on other competition variables have similar economic magnitude. Overall, the results suggest that competitive threats faced by a firm could predict the probability that the firm will experience large stock price declines in the following year.

In Panel B, we report the OLS regression results with *Ncskew* as the dependent variable. The results again give positive and significant coefficients on all of the four competition measures. Specifically, the coefficient on *Fluidity* is 0.166. This translates into a 0.033 (0.166×0.2) change in the *Ncskew* when *Fluidity* changes by one standard deviation of 0.2. The magnitude is large compared to the mean *Ncskew* of 0.018. Similarly, the economic magnitude is 0.03 (0.104×0.287) for *r_Fluidity*. In addition, a one standard deviation (0.448) increase in *Pctcomp* is associated with an increase of

0.016 (0.036×0.448) in *Ncskew*, and the economic magnitude on *r_comp* is the same at 0.016 (0.055×0.287).

[Table 2 here]

The coefficients on the control variables are consistent with previous studies, except for the sign on *Roa*. Despite the negative correlation revealed by previous literature, both the correlation (Table 1, Panel B) and the regression (Table 2) show that *Roa* is positively correlated with crash risk. The positive correlation could be explained by the stochastic bubble model in Chen, Hong, and Stein (2001); that is, high profitability and high stock returns indicate a "bubble" built up, so that there is a larger price drop when the bubble pops.[7] In unreported analysis, we attempt different measures of profitability (including return on equity, net income divided by sales, and alternative measures of *Roa*), and the positive relation remains. Finally, besides the control variables reported in the paper, we include additional control variables, liquidity and return kurtosis, in robustness analysis. The unreported results show that both liquidity and kurtosis are positively related to crash risk and the positive sign on the competition measures remains.

Overall, our regression results reveal a positive relation between competitive pressure and firms' crash risk. Endogeneity issues, however, may exist. Omitted variables such as unobserved firm strategy could affect a firm's competitive position and crash risk at the same time. Reverse causality may also be an issue; a firm experiencing high crash risk might be more vulnerable to predation by rivals. The next sections attempt to address the endogeneity issue, using an IV approach and a natural experiment.

3.3 Evidence from the IV regression

[7] The positive sign on *Roa* is also consistent with our information concealing story. Firms may hide bad information, resulting in inflated *Roa* and share price. The inflated share price then leads to stock crash when bad information is released.

Following Xu (2012), we use two instrumental variables, industry-level import tariff (*Tariff*) and foreign exchange rate (*Exrt*), for the competition variable *Fluidity*. The descriptive statistics of these instrumental variables are in Table 1 Panel A.

Data availability only allows us to run the IV regression for U.S. manufacturing firms (2000≤SIC≤3999) during 1998-2005. We first show that these manufacturing firms are not a special subsample in that the effect of *Fluidity* is similar to that in the whole sample. Columns (1) and (2) in Table 3 show that the marginal effect of *Fluidity* on *Crash* is 0.041 and that on *Ncskew* is 0.109, slightly weaker than those in the full sample. In the first stage of the IV regression, we regress *Fluidity* on tariffs, exchange rates, firm controls and fixed effects in Column (5) and find that both tariff and exchange rates are significant in predicting *Fluidity*. The negative sign on tariff indicates that higher tariff rates reduce competition from foreign rivals, and the positive sign on the exchange rate indicates that higher exchange rates make foreign goods cheaper and thus facilitate the entry of foreign rivals. The F-statistic for the hypothesis that the instruments are jointly zero is 25.77, suggesting that the IVs are significantly related to market competition and the relevance condition for IVs is satisfied.

[Table 3 here]

We then replace *Fluidity* with the predicted value of *Fluidity* from the first-stage regression, and generate the IV estimates in Columns (3) and (4) of Table 3. The Hansen J-statistics are insignificant with p-values of 0.81 and 0.24. This indicates that the instruments are appropriately uncorrelated with the disturbance process of the model and thus satisfy the exclusion condition.[8] We also conduct the Anderson-Rubin (AR) test.

[8] The Hansen's J-statistic is a test of the overidentifying restrictions and also a test of zero correlation between the instruments and the error term. The J-statistic is the value of the GMM objective function

This test is used to test the significance of endogenous variables and is robust to weak instruments. A significant AR chi-sqr statistic indicates that the effect of the endogenous variable *Fluidity* in the model is indeed significantly different from zero, and that our IV estimates are robust to weak instruments.

Our Probit, OLS, and IV regressions show that competitive pressure could lead to higher crash risk. The results are consistent with the information concealing hypothesis that greater competitive threats motivate the managers to hide unfavorable information and information hiding leads to future stock price crash. Note, however, that our IV regressions are not without limitations. As Xu (2012) points out, the inclusion of industry and year fixed effects in the first stage of the IV regression could restrict the power of the tests because the two instruments we use are industry-level variables. To further establish the causal relationship between competitive pressure and crash risk, we use the exogenous reductions of import tariff rates as natural experiments.

3.4 Evidence from the natural experiment

[Table 4 here]

Our natural experiment sample contains 3,108 firm-year observations in 1,037 U.S. manufacturing firms over the period of 1991-1997. Table 4 shows the summary statistics for the main and control variables, based on the three years surrounding the exogenous reductions of import tariff rates. The statistics show that for the entire sample, crash risk increases on average after tariff reductions. In Table 5, we separately examine the

evaluated at the GMM estimator. J is zero for any exactly identified equation, and positive for an overidentified equation. If J is "too large", doubt is cast on the satisfaction of the GMM moment conditions. Under the null hypothesis that all instruments are uncorrelated with the error term, the test has a large-sample chi-sqr (r) distribution, where r is the number of overidentifying restrictions (number of instruments – number of endogenous variables = 1 in our case). A rejection of the null hypothesis implies that the instruments do not satisfy the required orthogonality conditions – either because they are not truly exogenous or because they are being incorrectly excluded from the regression.

changes in crash risk for untreated firms and treated firms based on different magnitudes (Cut #x) of tariff reductions. In Panel A, the untreated and treated firms have similar crash ratio during the three years before tariff reduction, and the ratio increases more for treated firms and with larger tariff cuts. We find similar pattern in our second measure of crash risk, *Ncskew*, in Panel B.

[Table 5 here]

In Table 6, we control for firm characteristics using propensity score matching. We focus on the extreme cut in tariff rates, i.e. Cut #5. Sixteen tariff reductions are classified as Cut #5 during 1990-1997. These reductions are related to 177 firm-year observations. We match these observations with untreated firms (those unaffected by any tariff cut, i.e., Cut #1-5=0) on firm size, Tobin's Q, market leverage, Roa, Ret, Sigma, Dturn, and Ncskew in the pre-event window. The matching results in 150 valid matches, with 150 treated and 149 matched firms (one control firm is used twice). The matching method requires that matched firms and treated firms are similar. In Table 6 Panel A, we conduct a balance test to verify that matched and treated firms are balanced on pre-treatment covariates. The results shows that treated firms and matched control firms do not significantly differ from each other in all of our matching dimensions.

[Table 6 here]

After we obtain a valid matching sample, we compute the treatment effect using the difference-in-differences (DID) approach. According to Roberts and Whited (2012), the key assumption for consistency of the DID estimator is the parallel trend assumption. Specifically, this assumption requires any trends in outcomes (i.e., crash variables) for the treatment and control groups prior to treatment (i.e., tariff reduction) to be the same. To check that our data satisfy the parallel trend assumption, we perform statistical tests of the mean and median differences in average growth rates of the outcome variables between the treated group and the matched group. The statistical tests in Panel B of Table 6 show that the pre-event growth rates of the outcome variables do not differ significantly across the two groups. The test results suggest that the treated and the control samples present similar pre-treatment growing trends in the outcome variables. In unreported analysis, we also plot the outcome variables averaged for each year during the pre- and post-treatment periods, separately for the treated and the control firms. The figures (available upon request) show that the trends of *Ncskew* and *Crash* are similar for treated and control firms in the pre-event period, but diverge after the tariff reduction. This visual test further confirms that our sample meets the parallel trend assumption.

After verifying the matching sample validity and the parallel trend assumption, in Panel C of Table 6, we conduct the DID analysis using the treated sample and the propensity score matched counterfactuals. The DID analysis differences out unobserved firm heterogeneities for treated and matched firms, by taking the difference before and after the treatment for each firm. The analysis then filters out unobserved time effects by taking the difference of the differences. The results show that the increase in *Crash* ratio in treated firms is 0.062 higher than that in control firms and the difference is significant at 1% level. The number can be compared with the mean *Crash* of 0.184. We also find that the average treatment effect (ATT) of tariff cut on *Ncskew* is 0.188 and its t-statistic is 2.95. The effect is economically significant, considering that the mean *Ncskew* is 0.018 and the standard deviation is 0.813. Overall, by exploiting the exogenous shock in import tariff rates in the U.S. manufacturing firms, we establish causality from competitive threats to firm crash risk.

4. Exploring the Information Channel

So far our results establish a positive link between competition and stock crash. We argue that this link is consistent with the following hypothesis. Product market threats induce firm managers to hide bad news. When bad news is concealed till a threshold, the accumulated bad news is released and causes a large negative reaction in the stock market. This argument requires that firms facing competitive threats withhold unfavorable information. In this section, we provide direct evidence on the information channel through which product market threats affect crash risk.

4.1 Bad news withholding

We conduct two separate empirical tests to investigate managers' bad news withholding. First, we obtain managers' forecasts of quarterly EPS from First Call, and compare these forecasts with analyst consensus for the same period. We categorize managers' earnings forecasts as positive (negative) if managers' forecasts are higher (lower) than analyst consensus. If managers provide more positive and less negative earnings forecasts relative to analysts' forecasts, these managers are possibly hiding unfavorable firm-specific information. We construct three annual variables: the number of positive forecasts for the year (Pos_num), the number of negative forecasts (Neg_num), and the percent of negative forecasts out of the total number of management earnings forecasts (Neg_pct). We regress these three variables on product market threats. The results show that when product market threats become more severe, managers provide more positive and less negative forecasts in both the same year and the following year (Table 7 Panel

A). This is consistent with managers' increased tendency to withhold bad news when facing more threats from rivals.[9]

Next, we use four financial report readability variables provided by Li (2008) to proxy for managers' information withholding. Based on Li (2008), managers strategically use less readable and longer annual reports to make information less transparent and to hide adverse information from investors (p.225, 245). Rogers, Schrand, and Zechman (2014) employ Li's (2008) readability variables to capture managers' adverse news withholding. Specifically, Li (2008) provides *Fog*, *NegFlesch*, and *Kincaid* as measures of financial report readability, with higher values indicating less readable financial report. Li (2008) also provides *Length*, the logarithm of the number of words in the annual report. A longer report is more deterring and more difficult to read. Our results find that more competitive threats are associated with reduced readability of financial reports (greater *Fog*, *NegFlesch*, *Kincaid*, and *Length*) in both the concurrent year and the following year (Table 7 Panel B). This suggests that firms facing more threats are more likely to withhold adverse information.

We acknowledge that using management earnings forecasts and financial report readability to proxy for managers' bad news withholding is not perfect. Our results, nevertheless, provide suggestive evidence that managers withhold bad news when facing competitive threats from the product market.

[Table 7 here]

[9] The caveat with the analysis using management earnings forecasts is below. Positive management forecasts might not be due to that managers hide adverse news, but be due to that managers possess more favorable private information than analysts do. First, firms facing stronger threats from rivals may be less likely to have favorable information. Second, if positive forecasts are caused by favorable information, we should expect that the effect of competitive threats on management earnings forecasts is stronger in well-performed firms (which have more good news) than in poorly performed firms. In unreported analysis, we separately investigate the effect of competitive threats on management earnings forecasts, conditional on firm performance. We do not find that the results for good firms are stronger than those for bad firms.

4.2 Competition positions

If bad news withholding is the channel through which competition affects crash, we should see that firms with weaker positions in market competition are more vulnerable to stock crash. If a firm is operating at a favorable position, i.e. its market share is high or the industry the firm is at is concentrated, the firm might not be severely impacted due to the buffer provided by high profit margins. In contrast, firms with disadvantaged positions are more likely to have bad news or to be influenced by unfavorable information. Such bad news, when concealed, accumulated, and later detected, makes a firm more vulnerable to stock crash. Consequently, we expect the effect of *Fluidity* on crash risk to be more pronounced in the firms with less favorable market positions.

To test the above argument, we split the sample into high and low market share groups, according to the sales ration over the 3-digit SIC industry. We define *Share* to be one for firms with high market share, and zero otherwise. We then include *Share* and its interaction with *Fluidity* in the regressions. We expect to observe a negative coefficient on the interaction term, which suggests that higher market shares reduce firms' bad news hoarding. Besides market shares, we examine the degree of concentration using the HHI by the text-based network industry classification (TNIC3HHI) (developed by Hoberg and Phillips (2010a,b) and available from the Hoberg-Phillips Data Library). We define *Tnic* as an indicator equal to one, if the firm has a TNIC3HHI higher than the sample median, and zero otherwise. We interact the indicator with *Fluidity* and include them in the regression. Table 8 Panel A shows that the positive effect of competitive threats on crash risk is weaker for firms with more market shares and weaker in more concentrated markets.

[Table 8 here]

4.3 Financial constraints

We further investigate the role of financial constraints in the relation between competitive threats and crash risk. Tighter financial constraints imply difficulty in funding positive NPV projects to gain advantages over potential or existing competitors (Campello, 2006). In addition, financially constrained firms are more vulnerable to aggressive pricing and production strategies adopted by their competitors. Moreover, firms with financial constraints may have incentives to hide negative information in order to obtain financing at a lower cost. Consequently, we expect financially constrained firms to have more adverse information and thus will be affected by market competition more than the unconstrained firms.

We rely on three measures of financial constraints, HP index (Hadlock and Pierce, 2010), WW index (Whited and Wu, 2006), and dividend paying indicator. We categorize firms with the HP and WW indices above sample medians as having more financial constraints. We also split the sample by whether a firm pays dividends because a dividend payer is less financially constrained (Denis and Sibilkov, 2010). The results in Table 8 Panel B find that financial constraints aggravate the effect of competitive pressure on crash risk.

4.4 Information asymmetry

According to Kothari, Shu, and Wysocki (2009), firms are better able to hide bad news in an opaque information environment. Hutton, Marcus, and Tehranian (2009) empirically document that opaque stocks are more likely to crash. We thus expect to see that the impact of product market threats on crash risk is more severe when there is less transparent information about the firm. We split the sample into high and low information asymmetry groups, according to firm size, age, and volatility. Table 8 Panel C shows that the effect of competition on crash risk is stronger in smaller, younger, and more volatile firms. This result suggests that bad news hoarding caused by competitive threats is more severe in opaque firms.

4.5 Long-run effect

As we argue, stock crash occurs when hidden bad information gets released all at once. Bad information could be accumulated and concealed for a long period. If information is the channel through which competition affects crash, we may see that competition impacts not only shorter-term (such as one-year-ahead) crash risk (as in Tables 2 and 3), but also longer-term crash risk. We investigate this issue in this section.

We regress the one-year-ahead, two-year-ahead, and three-year-ahead crash measures on our key independent variable, *Fluidity*, in OLS and Probit regressions. Table 9 reports the results. For fair comparisons, all the regressions require that the sample has non-missing information on the year t, t+1, and t+2 crash risk. Our regression results show that the impact of *Fluidity* on crash risk generally remains significant at least three years after *Fluidity* changes. The effect, however, diminishes over the years, with the most significant impact occurring within one year after the product market threats increase. In all, the results show a lasting impact of competitive threats on crash risk, and more importantly, the results shed light on how accumulated information gets revealed over time.

[Table 9 here]

4.6 Earnings torpedo effect

Skinner and Sloan (2002) show that growth stocks present an earnings torpedo effect. That is, missing analysts' forecasts, even by small amounts, causes disproportionately large stock price declines in growth firms but not in value firms. The torpedo effect could lead to stock crash. To disentangle the effect of earnings torpedo on crash risk from the effect of product market threats, we control for the market-to-book ratio in all our specifications because the earnings torpedo effect is present mostly in growth stocks (Skinner and Sloan, 2002). In addition, in unreported tests, we conduct a subsample analysis by firms' market-to-book ratios. We find that our results of product market threats being positively associated with crash risk are significant in both growth stocks and value stocks. Therefore, our results are not limited to growth stocks and the earnings torpedo effect is unlikely to be the reason that drives our results.

5. Conclusions

This paper examines the effect of product market threats on firms' stock price crash risk. Using fluidity as the main measure of the product market threats, the regressions find that firms facing more threats from the product market are more prone to stock price crash. This result is further confirmed by an IV analysis and a difference-in-difference analysis with exogenous shock to market competition. Market competition reduces information disclosure due to the proprietary cost in the product market and the pressure from the capital market. Firms facing stronger product market threats may thus hoard bad information. Such information concealing behavior engenders stock price crashes when bad information cannot be concealed and finally becomes public. Our results suggest that competition may adversely affect the financial market by increasing the likelihood of large stock price declines.

References

Aghion, Philippe, Nick Bloom, and Richard Blundell, 2005, Competition and Innovation: An Inverted-U Relationship, *Quarterly Journal of Economics*, 120-2, 701-28

Ali, Ashiq, Sandy Klasa, and Eric Yeung, 2009, The Limitations of Industry Concentration Measures Constructed with Compustat Data: Implications for Finance Research, *Review of Financial Studies*, 22-10, 3839-71

Anderson, James E., and Eric van Wincoop, 2004, Trade Costs, *Journal of Economic Literature*, 42-3, 691-751

Ang, Andrew, Joseph Chen, Yuhang Xing, 2006, Downside Risk, *Review of Financial Studies*, 19-4, 1191-239

Anilowski, Carol, Mei Feng, and Douglas J. Skinner, 2007, Does Earnings Guidance Affect Market Returns? The Nature and Information Content of Aggregate Earnings Guidance, *Journal of Accounting and Economics*, 44, 36-63

Bali, Turan G., Nusret Cakici, Robert F. Whitelaw, 2014, Hybrid Tail Risk and Expected Stock Returns: When Does the Tail Wag the Dog?, *Review of Asset Pricing Studies*, 4-2, 206-46

Bernard, Andrew B., J. Bradford Jensen, Stephen J., Redding, and Peter K. Schott, 2007, Firms in International Trade, *Journal of Economic Perspective*, 21-3, 105-30

Campello, Murillo, 2006. Debt Financing: Does it Boost or Hurt Firm Performance in Product Markets?, *Journal of Financial Economics*, 82-1, 135-72

Chang, Bo Young, Peter Christoffersen, and Kris Jacobs, 2013, Market Skewness Risk and the Cross Section of Stock Returns, *Journal of Financial Economics,* 107, 46-68

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2001, Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices, *Journal of Financial Economics*, 61, 345-81

Darrough, Masako N., 1993. Disclosure Policy and Competition: Cournot vs. Bertrand, *Accounting Review*, 68-3, 534-61

Dedman, Elisabeth, and Clive Lennox., 2009, Perceived Competition, Profitability and the Withholding of Information about Sales and the Cost of Sales, *Journal of Accounting and Economics*, 48-2,3, 210-30

Denis, David J. and Valeriy Sibilkov, 2010, Financial Constraints, Investment, and the Value of Cash Holdings, *Review of Financial Studies*, 23-1, 247-69

Dhaliwal, Dan, Shawn Huang, Inder K. Khurana, and Raynolde Pereira, 2014, Product Market Competition and Conditional Conservatism, *Review of Accounting Studies*, 1-37

Dimson, Elroy, 1979, Risk Measurement When Shares are Subject to Infrequent Trading, *Journal of Financial Economics*, 7, 197-226

Duso, Tomaso, and Lars-Hendrik Roller, 2003, Endogenous Deregulation: Evidence from OECD Countries, *Economics Letters*, 81, 67-71

Ellis, Jesse A., C. Edward Fee, and Shawn E. Thomas. 2012, Proprietary Costs and the Disclosure of Information about Customers, *Journal of Accounting Research*, 50-3, 685-727

Feenstra, Robert C., 1996, U.S. Imports, 1972-1994: Data and Concordances, NBER working paper

Feenstra, Robert C., John Romalis, and Peter K. Schott, 2002, U.S. Imports, Exports, and Tariff Data, 1989-2001, NBER working paper

Fresard, Laurent, 2010, Financial Strength and Product Market Behavior: The Real Effects of Corporate Cash Holdings, *Journal of Finance*, 65-3, 1097-122

Galdon-Sanchez, Jose E., and James A. Schmitz, Jr., 2002, Competitive Pressure and Labor Productivity: World Iron-Ore Markets in the 1980's, *American Economic Review*, 92-4, 1222-35

Gennotte, Gerard, and Hayne Leland, 1990, Market Liquidity, Hedging, and Crashes, *American Economic Review*, 80-5, 999-1021

Graham, John R., Campbell Harvey, and Shiva Rajgopal, 2005, The Economic Implications of Corporate Financial Reporting, *Journal of Accounting and Economics*, 40-1, 3-73

Hadlock, Charles J., and Joshua R. Pierce, 2010, New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index, *Review of Financial Studies*, 23-5, 1909-40

Hart, Oliver D., 1983, The Market Mechanism as an Incentive Scheme, *The Bell Journal of Economics*, 14-2, 366-82

Hoberg, Gerard, and Gordon Phillips, 2010a, Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis, *Review of Financial Studies*, 23-10, 3773-811

Hoberg, Gerard, and Gordon Phillips, 2010b, Real and Financial Industry Booms and Busts, *Journal of Finance*, 65-1, 45-86

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product Market Threats, Payouts, and Financial Flexibility, *Journal of Finance*, 69-1, 293-324

Hong, Harrison, and Jeremy C. Stein, 2003, Differences of Opinion, Short-Sales Constraints, and Market Crashes, *Review of Financial Studies*, 16-2, 487-525

Hou, Kewei, and David T. Robinson, 2006, Industry Concentration and Average Stock Returns, *Journal of Finance*, 61-4, 1927-56

Huang, Jennifer, and Jiang Wang, 2009, Liquidity and Market Crashes, *Review of Financial Studies*, 22-7, 2407-43

Hutton, Amy P., Alan J. Marcus, and Hassan Tehranian, 2009, Opaque Financial Reports, R^2, and Crash Risk, *Journal of Financial Economics*, 94, 67-86

Irvine, Paul J., and Jeffrey Pontiff, 2009, Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition, *Review of Financial Studies*, 22-3, 1149-77

Jin, Li, and Stewart C. Myers, 2006, R^2 around the World: New Theory and New Tests, *Journal of Financial Economics,* 79-2, 257-92

Kelly, Bryan, and Hao Jiang, 2014, Tail Risk and Asset Prices, *Review of Financial Studies*, 2841-71

Kim, Oliver, 1999, Discussion of the Role of the Manager's Human Capital in Discretionary Disclosure, *Journal of Accounting Research,* 37, 183-85

Kim, Jeong-Bon, Yinghua Li, and Liandong Zhang, 2011a, Corporate Tax Avoidance and Stock Price Crash Risk: Firm-Level Analysis, *Journal of Financial Economics*, 100, 639-62

Kim, Jeong-Bon, Yinghua Li, and Liandong Zhang, 2011b, CFOs versus CEOs: Equity Incentives and Crashes, *Journal of Financial Economics*, 101, 713-30

Kim, Jeong-Bon, and Liandong Zhang, 2015, Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence, *Contemporary Accounting Research*, forthcoming

Kothari, S. P., Susan Shu, and Peter D. Wysocki, 2009, Do Managers Withhold Bad News?, *Journal of Accounting Research*, 47-1, 241-76

Li, Feng, 2008, Annual Report Readability, Current Earnings, and Earnings Persistence, *Journal of Accounting and Economics*, 45, 221-47

Li, Feng, Russell Lundholm, and Michael Minnis, 2013, A Measure of Competition Based on 10-K Filings, *Journal of Accounting Research*, 51-2, 399-436

Roberts, Michael R., and Toni M. Whited, 2012, Endogeneity in Empirical Corporate Finance, in George Constantinides, Milton Harris, and Rene Stulz, eds. *Handbook of the Economics of Finance* Volume 2, Elsevier

Rogers, Jonathan L., Catherine Schrand, and Sarah L. C. Zechman, 2014, Do Managers Tacitly Collude to Withhold Industry-Wide Bad News?, working paper, University of Colorado, University of Pennsylvania, and University of Chicago

Schott, Peter K., 2010, U.S. Manufacturing Exports and Imports by SIC or NAICS Category and Partner Country, 1972 to 2005, working paper, Yale University

Schmidt, Klaus M., 1997, Managerial Incentives and Product Market Competition, *Review of Economic Studies*, 64, 191-213

Shleifer, Andrei, 2004, Does Competition Destroy Ethical Behavior?, *American Economic Review*, 94-2, 414-418

Skinner, Douglas J., and Richard G. Sloan, 2002, Earnings Surprises, Growth Expectations, and Stock Returns or Don't Let an Earnings Torpedo Sink Your Portfolio, *Review of Accounting Studies*, 7, 289-312

Syverson, Chad, 2011, What Determines Productivity?, *Journal of Economic Literature*, 49-2, 326-65

Tybout, James R., 2003, Plant- and Firm-Level Evidence on "New" Trade Theories, In: Choi, K., Harrigan, J. (Eds.), *Handbook of International Trade*, Basil-Blackwell, Oxford, 388-415

Valta, Philip, 2012, Competition and the Cost of Debt, *Journal of Financial Economics*, 105, 661-82

Verrecchia, Robert E., 1983, Discretionary Disclosure, *Journal of Accounting and Economics*, 5-1, 179-94

Whited, Toni M., and Guojun Wu, 2006, Financial Constraints Risk, *Review of Financial Studies*, 19-2, 531-59

Xu, Jin, 2012, Profitability and Capital Structure: Evidence from Import Penetration, *Journal of Financial Economics*, 106, 427-46

Table 1
Summary Statistics and Correlations

The table reports the descriptive statistics and correlation matrix for crash risk, product market threats, and control variables. The measures of crash risk are *Crash* and *Ncskew*. The main measure for product market threats is *Fluidity* developed by Hoberg, Phillips, and Prabhala (2014). The alternative competition measures include *r_Fluidity*, *pctcomp*, and *r_comp*. The sample contains 27,995 unique firm-years for 4,759 publicly traded U.S. firms over the period from 1998 to 2009. Panel A reports the summary statistics and Panel B the correlations. Variable definitions are in Appendix A. All variables are winsorized at 1% and 99%. In Panel B, p-values are in parentheses.

Panel A: Summary statistics

Variable Type	Variable	Obs	Mean	Std	p25	Median	p75
Dependent Variable	$Crash_t$	27995	0.184	0.388	0	0	0
	$Ncskew_t$	27995	0.018	0.813	-0.450	-0.017	0.425
Independent Variable: Main	$Fluidity_{t-1}$	27995	0.406	0.2	0.255	0.373	0.523
Instrumental Variables	$Tariff_{t-1}$	11955	0.011	0.019	0.001	0.004	0.012
	$Exrt_{t-1}$	15379	0.101	0.084	0.05	0.07	0.123
Independent Variable: Alternative	$r\_Fluidity_{t-1}$	27995	0.545	0.287	0.3	0.5	0.8
	$Pctcomp_{t-1}$	17285	0.546	0.448	0.225	0.403	0.733
	r_comp_{t-1}	17285	0.549	0.287	0.3	0.5	0.8
Control Variables	$Dturn_{t-1}$	27995	0.008	0.106	-0.025	0.002	0.036
	$Sigma_{t-1}$	27995	0.067	0.034	0.042	0.06	0.085
	Ret_{t-1}	27995	-0.281	0.308	-0.356	-0.175	-0.085
	$Size_{t-1}$	27995	5.703	1.886	4.329	5.599	6.965
	MB_{t-1}	27995	2.099	1.702	1.121	1.538	2.371
	Lev_{t-1}	27995	0.139	0.158	0.003	0.085	0.222
	Roa_{t-1}	27995	0.079	0.179	0.047	0.114	0.17

Table 1
Summary Statistics and Correlations (Continued)

Panel B: Correlations

	Crash	Ncskew	Fluiditiy	r_Fluidity	Pctcomp	r_comp	Dturn	Ncskew	Sigma	Ret	Size	MB	Lev
$Crash_t$	1												
$Ncskew_t$	0.64	1											
	(0.00)												
$Fluidity_{t-1}$	0.03	0.05	1										
	(0.00)	(0.00)											
$r\_Fluidity_{t-1}$	0.03	0.05	0.95	1									
	(0.00)	(0.00)	(0.00)										
$Pctcomp_{t-1}$	0.00	0.00	0.12	0.14	1								
	(0.69)	(0.94)	(0.00)	(0.00)									
r_comp_{t-1}	0.03	0.01	0.16	0.18	0.77	1							
	(0.00)	(0.18)	(0.00)	(0.00)	(0.00)								
$Dturn_{t-1}$	0.03	0.07	-0.01	-0.01	-0.05	-0.04	1						
	(0.00)	(0.00)	(0.17)	(0.24)	(0.00)	(0.00)							
$Ncskew_{t-1}$	0.02	0.04	0.04	0.05	-0.02	0.01	0.02	1					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.38)	(0.01)						
$Sigma_{t-1}$	-0.05	-0.05	0.27	0.29	0.32	0.17	0.12	0.02	1				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
Ret_{t-1}	0.05	0.06	-0.23	-0.25	-0.28	-0.14	-0.14	0.03	-0.96	1			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
$Size_{t-1}$	0.05	0.12	-0.08	-0.08	-0.29	-0.26	0.07	0.14	-0.47	0.41	1		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
MB_{t-1}	0.06	0.11	0.29	0.27	0.11	0.11	0.16	-0.01	0.12	-0.12	-0.11	1	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	(0.00)		
Lev_{t-1}	-0.05	-0.07	-0.19	-0.19	-0.11	-0.21	-0.01	-0.02	-0.01	0.02	0.21	-0.40	1
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	
Roa_{t-1}	0.06	0.09	-0.37	-0.32	-0.08	-0.11	0.08	0.06	-0.39	0.38	0.36	-0.14	0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 2
Probit and OLS Regressions

The table reports the regression results on the effect of competition pressure on crash risk. Panel A shows the marginal effects of competitive threats on the *Crash* indicator from the Probit regressions. Panel B shows the OLS regression results on the effect of competitive threats on *Ncskew*. Column (1) shows the result using *Fluidity* as the main independent variable. Columns (2)-(4) employ alternative measures of competitive pressure. Variable definitions are in Appendix A. Standard errors adjusting for heteroskedasticity and within-firm clustering are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Dependent variable = $Crash_t$

Variable Type	Variables	(1)	(2)	(3)	(4)
Independent Variable: Main	$Fluidity_{t-1}$	0.066***			
		[0.015]			
Independent Variables: Alternative	$r\_Fluidity_{t-1}$		0.043***		
			[0.010]		
	$Pctcomp_{t-1}$			0.022***	
				[0.008]	
	r_comp_{t-1}				0.030***
					[0.011]
Control Variables	$Dturn_{t-1}$	0.093***	0.093***	0.086***	0.086***
		[0.023]	[0.023]	[0.032]	[0.032]
	$Ncskew_{t-1}$	0.003	0.003	-0.003	-0.003
		[0.003]	[0.003]	[0.004]	[0.004]
	$Sigma_{t-1}$	0.947***	0.951***	2.079***	2.056***
		[0.305]	[0.305]	[0.424]	[0.423]
	Ret_{t-1}	0.131***	0.132***	0.258***	0.255***
		[0.032]	[0.032]	[0.048]	[0.048]
	$Size_{t-1}$	0.008***	0.008***	0.012***	0.012***
		[0.002]	[0.002]	[0.002]	[0.002]
	MB_{t-1}	0.007***	0.007***	0.008***	0.008***
		[0.002]	[0.002]	[0.002]	[0.002]
	Lev_{t-1}	-0.047**	-0.047**	-0.037	-0.037
		[0.019]	[0.019]	[0.023]	[0.024]
	Roa_{t-1}	0.146***	0.140***	0.229***	0.230***
		[0.018]	[0.017]	[0.033]	[0.033]
Year Fixed Effects		Yes	Yes	Yes	Yes
Industry Fixed Effects		Yes	Yes	Yes	Yes
# of Observations		27,995	27,995	17,284	17,284
Pseudo R^2		0.0273	0.0272	0.0317	0.0317

Table 2
Probit and OLS Regressions (Continued)

Panel B : Dependent variable = $Ncskew_t$					
Variable Type	**Variables**	(1)	(2)	(3)	(4)
Independent Variable: Main	$Fluidity_{t-1}$	0.166***			
		[0.033]			
Independent Variables: Alternative	$r\_Fluidity_{t-1}$		0.104***		
			[0.022]		
	$Pctcomp_{t-1}$			0.036**	
				[0.016]	
	r_comp_{t-1}				0.055**
					[0.022]
Control Variables	$Dturn_{t-1}$	0.298***	0.298***	0.251***	0.251***
		[0.048]	[0.048]	[0.063]	[0.063]
	$Ncskew_{t-1}$	0.008	0.008	0.004	0.004
		[0.007]	[0.007]	[0.008]	[0.008]
	$Sigma_{t-1}$	4.633***	4.665***	5.720***	5.679***
		[0.600]	[0.600]	[0.776]	[0.776]
	Ret_{t-1}	0.502***	0.505***	0.620***	0.615***
		[0.059]	[0.059]	[0.080]	[0.080]
	$Size_{t-1}$	0.055***	0.055***	0.057***	0.057***
		[0.004]	[0.004]	[0.004]	[0.004]
	MB_{t-1}	0.037***	0.037***	0.041***	0.040***
		[0.003]	[0.003]	[0.005]	[0.005]
	Lev_{t-1}	-0.286***	-0.287***	-0.292***	-0.293***
		[0.038]	[0.038]	[0.047]	[0.047]
	Roa_{t-1}	0.325***	0.312***	0.437***	0.438***
		[0.035]	[0.035]	[0.063]	[0.063]
	Constant	-0.747***	-0.742***	-0.774***	-0.795***
		[0.044]	[0.044]	[0.057]	[0.058]
Year Fixed Effects		Yes	Yes	Yes	Yes
Industry Fixed Effects		Yes	Yes	Yes	Yes
# of Observations		27,995	27,995	17,285	17,285
Adjusted R^2		0.057	0.057	0.056	0.056

Table 3
2SLS Regressions

The table presents the regression results on the effect of competition on crash risk, using the instrumental variable approach. The instrumental variables for competition include the import tariff rate and the real effective exchange rate at the three-digit SIC level. Because these IVs are available for manufacturing firms (SIC 2000-3999) only, the regressions in this table are conducted on manufacturing firms. Columns (1)-(2) are the Probit and OLS regressions based on the manufacturing firms and these results will be compared with the 2SLS results in (3) and (4). Columns (3)-(4) present the second-stage regression results and Column (5) reports the first-stage estimation. The estimates in Columns (1) and (3) are marginal effects. Variable definitions are in Appendix A. Standard errors adjusting for heteroskedasticity and within-firm clustering are in brackets (clustering standard errors at the industry level gives similar results). *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

	Probit	OLS	IV Second-stage estimation		IV First-stage estimation
Variables	(1) LHS = $Crash_t$	(2) LHS = $Ncskew_t$	(3) LHS = $Crash_t$	(4) LHS = $Ncskew_t$	(5) LHS = $Fluidity_{t-1}$
$Fluidity_{t-1}$	0.041**	0.109**	0.344**	0.642**	
	[0.020]	[0.044]	[0.148]	[0.310]	
$Tariff_{t-1}$					-2.731***
					[0.381]
$Exrt_{t-1}$					0.093**
					[0.044]
$Dturn_{t-1}$	0.079**	0.258***	0.108***	0.291***	-0.105***
	[0.031]	[0.065]	[0.039]	[0.082]	[0.014]
$Ncskew_{t-1}$	0.001	0.002	0.001	0.004	-0.003
	[0.004]	[0.009]	[0.005]	[0.011]	[0.002]
$Sigma_{t-1}$	1.010**	4.989***	-0.328	2.987	4.859***
	[0.401]	[0.794]	[0.907]	[1.853]	[0.252]
Ret_{t-1}	0.116***	0.491***	0.027	0.349**	0.356***
	[0.042]	[0.079]	[0.075]	[0.147]	[0.024]
$Size_{t-1}$	0.009***	0.055***	0.003	0.053***	0.025***
	[0.002]	[0.005]	[0.005]	[0.009]	[0.002]
MB_{t-1}	0.006***	0.031***	0.000	0.023***	0.016***
	[0.002]	[0.004]	[0.004]	[0.007]	[0.002]
Lev_{t-1}	-0.088***	-0.338***	-0.026	-0.246***	-0.182***
	[0.026]	[0.055]	[0.042]	[0.088]	[0.019]
Roa_{t-1}	0.110***	0.258***	0.211***	0.435***	-0.288***
	[0.021]	[0.045]	[0.049]	[0.103]	[0.016]
Constant		-0.708***		-0.732***	0.122***
		[0.057]		[0.091]	[0.030]
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
# obs	15,846	15,846	11,955	11,955	11,955
Adjusted / Pseudo R^2	0.02	0.05		0.045	0.509
P-value of Hansen's J-statistic			0.81	0.24	
Anderson-Rubin (A-R) test (robust to weak instruments)		χ^2 statistic (p-value)	8.53 (0.01)	5.96 (0.05)	
Test: IVs jointly equal to zero			F-statistic (p-value)		25.77 (0.00)

Table 4
Evidence from Natural Experiment: Summary Statistics

The table reports the descriptive statistics used in the difference-in-difference approach. The sample contains 3,108 observations, covering 1,037 firms during 1991-1997. *Crash_Dif* is the difference between the proportion of crash years during the three years after the tariff reduction and that during the three years before. *Ncskew_Dif* is the difference between the average of *Ncskew* three years after the tariff reduction and the average of *Ncskew* three years before. Variable definitions are in Appendix A. All variables are winsorized at 1% and 99% level.

Variables	Obs	Mean	Std	p25	Median	p75
Crash_Dif	3108	0.13	0.2	0	0	0.33
Ncskew_Dif	3108	0.02	0.56	-0.34	0.01	0.37
lag_dturn	3108	5.39	2.24	3.68	5.04	7.04
lag_sigma	3094	2.25	2.59	1.18	1.56	2.47
lag_ret	3085	0.13	0.13	0.02	0.1	0.21
lag_size	3103	0.1	0.18	0.08	0.13	0.19
lag_mb	3108	-0.19	0.18	-0.27	-0.13	-0.06
lag_lev	3108	0.06	0.03	0.03	0.05	0.07
lag_roa	2478	0.01	0.04	0	0	0.01
Ncskew_Pre	3108	-0.09	0.42	-0.35	-0.09	0.17

Table 5
Evidence from Natural Experiment: Raw Patterns

The table presents the impact of import tariff reductions on crash risk. The variable *Cut #x* is one if the reduction in the import tariff rate is at least x times the median tariff reduction in the same three-digit SIC industry, and zero otherwise. Untreated firms are those with import tariff reduction lower than the median tariff cut during the period [t, t+3], where year t is the year of tariff reduction. Panel A shows the change in the crash ratio for untreated firms and treated firms with different levels of tariff reduction. *Crash_Pre* is the proportion of crash years during the three years before the tariff reduction, and *Crash_Post* is that during the three years after. Panel B shows the raw pattern of change in *Ncskew* for untreated and treated firms with different levels of tariff reduction. *Ncskew_Pre* is the average of *Ncskew* three years before the tariff reduction, and *Ncskew_Post* the average three years after. Difference is the "post" variable minus the "pre" variable, and t-stat is the t-statistics for the differences. Variable definitions are in Appendix A.

Panel A: Three-year change in Crash Ratio

	# of Obs	Crash_Pre	Crash_Post	Difference	t-stat	std	p25	median	p75
Untreated	2579	0.003	0.128	0.125	30.124	0.210	0.000	0.000	0.333
Cut #1	529	0.002	0.134	0.132	14.533	0.208	0.000	0.000	0.333
Cut #2	361	0.003	0.139	0.137	12.177	0.213	0.000	0.000	0.333
Cut #3	218	0.005	0.153	0.148	9.590	0.228	0.000	0.000	0.333
Cut #4	183	0.005	0.160	0.155	8.959	0.234	0.000	0.000	0.333
Cut #5	177	0.006	0.164	0.158	8.922	0.236	0.000	0.000	0.333

Panel B: Three-year change in Ncskew

	# of Obs	Ncskew_Pre	Ncskew_Post	Difference	t-stat	std	p25	median	p75
Untreated	2579	-0.092	-0.073	0.019	1.765	0.545	-0.347	0.011	0.374
Cut #1	529	-0.093	-0.081	0.012	0.532	0.521	-0.314	-0.008	0.373
Cut #2	361	-0.087	-0.090	-0.003	-0.098	0.516	-0.322	-0.016	0.338
Cut #3	218	-0.083	-0.059	0.024	0.645	0.547	-0.308	-0.008	0.410
Cut #4	183	-0.084	-0.056	0.028	0.678	0.565	-0.308	0.016	0.450
Cut #5	177	-0.086	-0.052	0.034	0.800	0.563	-0.308	0.020	0.450

Table 6
Evidence from Natural Experiment: Propensity Score Matching

The table presents the impact of substantial reduction in import tariffs (Cut #5) on firms' crash risk, using the propensity score matching method. The variable *Cut #5* is one if the reduction in the import tariff rate is at least 5 times the median tariff reduction in the same three-digit SIC industry, and zero otherwise. Panel A shows the balance tests for treated firms and control firms in the matching dimensions, which include lag_size, lag_mb, lag_lev, lag_roa, lag_ret, lag_sigma, lag_dturn, and lag_Ncskew. In Panel B, for each firm, we calculate the annual growth rates of Ncskew and the Crash indicator for year -1 and year -2 (year 0 is the year of tariff reduction), and average the year -1 and year -2 growth rates for each crash variable. We then report the mean and median of the growth rates and the p-values associated with the test statistics for differences in means (standard t-test) and in medians (Wilcoxon signrank test) between treated firms and matched firms. Panel C shows the nearest-neighbor propensity matching results for *Crash* and *Ncskew*. Variable definitions are in Appendix A. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Balance tests

	# of Obs	Mean Treatment	Mean Control	% bias	p-value
lag_size	150	4.986	5.328	-16.8	0.115
lag_mb	150	2.075	1.885	8.9	0.186
lag_lev	150	0.127	0.150	-17.9	0.113
lag_roa	150	0.114	0.128	-7.9	0.429
lag_ret	150	-0.175	-0.162	-7.9	0.476
lag_sigma	150	0.053	0.051	10.9	0.340
lag_dturn	150	0.004	0.003	1.2	0.899
lag_Ncskew	150	-0.078	-0.015	-14.4	0.239

Panel B: Trends in firm crash risk for treated and matched firms: mean and median comparisons

		Avg.Growth	t-test (p-value)	Med. Growth	Signrank (p-value)
Ncskew	Treated	0.04	0.86	0.02	0.64
	Matched	0.05		0.04	
Crash Indicator	Treated	0.05	0.30	0.00	0.29
	Matched	0.02		0.00	

Panel C: Propensity score matching results

	Treated Firms		Nearest Neighbor Control Firms	Difference in Difference	
	# of Obs	Mean Difference (Post – Pre)	Mean Difference (Post – Pre)	Average Treatment Effect (ATT)	t-stat
Crash	150	0.153	0.091	0.062***	2.73
Ncskew	150	0.054	-0.133	0.188***	2.95

Table 7
Managers' Bad News Withholding

The table presents the impact of competition on managers' bad news withholding. In Panel A, we obtain managers' forecasts of quarterly EPS from First Call, and compare these forecasts with analyst consensus for the same period. We categorize managers' earnings forecasts as positive (negative) if managers' forecasts are higher (lower) than analyst consensus. Pos_num (Neg_num) is the number of managers' positive (negative) forecasts for the year. Neg_pct is the percent of managers' negative forecasts out of the total number of management earnings forecasts for the year. In Panel B, Fog, NegFlesch, and Kincaid are measures of financial report readability, with higher values indicating less readable financial report. Length is the logarithm of the number of words in the annual report. A longer report is more deterring and more difficult to read. Variable definitions are in Appendix A. Standard errors adjusting for heteroskedasticity and within-firm clustering are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Effect of Competitive Threats on Management Earnings Forecasts

	LHS at time t-1 and controls at time t-2			LHS at time t and controls at time t-1		
	(1) Poisson Pos_num_{t-1}	(2) Poisson Neg_num_{t-1}	(3) Tobit Neg_pct_{t-1}	(4) Poisson Pos_num_{t}	(5) Poisson Neg_num_{t}	(6) Tobit Neg_pct_{t}
$Fluidity_{t-1}$	0.324**	-0.09	-11.31*	0.222	-0.097*	-10.97*
	[0.149]	[0.060]	[6.752]	[0.148]	[0.056]	[6.109]
Size	0.030*	0.093***	0.555	0.004	0.086***	1.540**
	[0.016]	[0.007]	[0.771]	[0.016]	[0.006]	[0.735]
MB	0.038	-0.033***	-1.616	-0.023	-0.001	1.794*
	[0.027]	[0.011]	[1.296]	[0.025]	[0.007]	[0.968]
Lev	-0.005	-0.438***	-7.072	0.309	-0.453***	-21.79**
	[0.236]	[0.089]	[10.29]	[0.213]	[0.079]	[9.214]
Roa	2.678***	0.210*	-75.91***	0.419*	0.559***	5.427
	[0.326]	[0.118]	[13.83]	[0.244]	[0.087]	[9.951]
Constant	-0.549	-1.113***		-0.307	-0.202	
	[0.482]	[0.425]		[0.902]	[0.621]	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# obs.	5,693	5,693	5,693	6,405	6,405	6,405
Pseudo R^2	0.0627	0.0628	0.00974	0.0458	0.0624	0.00819

Panel B: Effect of Competitive Threats on Financial Report Readability								
	LHS at time t-1 and controls at time t-2				LHS at time t and controls at time t-1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fog_{t-1}	$NegFlesch_{t-1}$	$Kincaid_{t-1}$	$Length_{t-1}$	Fog_t	$NegFlesch_t$	$Kincaid_t$	$Length_t$
$Fluidity_{t-1}$	0.948***	3.403***	1.128***	0.802***	0.986***	3.264***	1.163***	0.781***
	[0.123]	[0.336]	[0.118]	[0.041]	[0.110]	[0.303]	[0.106]	[0.037]
Size	0.045***	0.238***	0.077***	0.125***	0.050***	0.215***	0.084***	0.127***
	[0.016]	[0.040]	[0.015]	[0.005]	[0.015]	[0.036]	[0.014]	[0.004]
MB	-0.014	-0.072**	-0.005	0.008**	-0.004	-0.052*	0.004	0.009**
	[0.011]	[0.030]	[0.010]	[0.004]	[0.010]	[0.027]	[0.010]	[0.003]
Lev	-0.250	-2.263***	-0.454***	0.322***	-0.087	-1.910***	-0.333**	0.318***
	[0.162]	[0.418]	[0.154]	[0.053]	[0.145]	[0.354]	[0.136]	[0.044]
Roa	-0.380***	-0.533*	-0.483***	-0.310***	-0.475***	-0.732**	-0.566***	-0.277***
	[0.118]	[0.323]	[0.114]	[0.041]	[0.122]	[0.315]	[0.116]	[0.036]
Constant	19.080***	-22.896***	14.909***	9.212***	19.022***	-22.235***	14.896***	8.975***
	[0.147]	[0.313]	[0.133]	[0.037]	[0.147]	[0.291]	[0.130]	[0.036]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# obs.	18,060	18,060	18,060	17,979	24,189	24,189	24,189	24,063
Adj. R^2	0.041	0.148	0.062	0.168	0.038	0.164	0.059	0.155

Table 8
Subsample Analysis

The table presents the subsample analysis of the impact of competition on crash risk. Panel A presents the results partitioned by incumbent firms' competition positions: market share and product market Herfindahl index. Share is an indicator variable that equals one if the firm has a market share greater than the sample median, and zero otherwise. Tnic is an indicator variable equal to 1 if the firm has a TNIC3HHI (Hoberg and Phillips, 2010a,b) higher than the sample median, and zero othrewise. Panel B presents the results partitioned by firms' financial constraints. We use three measures of financial constraints: HP Index (Hadlock and Pierce, 2010), WW Index (Whited and Wu, 2006), and dividend paying indicator. HP (WW) is an indicator variable equal to 1 if the firm has an HP (WW) index higher than the sample median, and zero otherwise. Dividend is an indicator variable equal to 1 if the firm pays dividends, and zero otherwise. Panel C presents the results partitioned by firms' information asymmetry. High Ret_vol is an indicator variable equal to one if the firm's stock return volatility is higher than the sample median, and zero otherwise. Large is an indicator variable equal to 1 if the firm is larger than the sample median, and zero otherwise. Old is an indicator variable equal to 1 if the firm's age is greater than the sample median, and zero otherwise. Variable definitions are in Appendix A. Standard errors adjusting for heteroskedasticity and within-firm clustering are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level. Control variables used in Table 2 are included in all the estimations, but suppressed for expositional convenience. In Panel C, the control variable sigma is excluded from Columns (1) and (4) because High Ret_vol is in the models, and firm size is excluded from Columns (2) and (5) because Large is in the models.

Panel A: Subsample Analysis by Competition Positions

Variables	(1) $Crash_t$	(2) $Crash_t$	(3) $Ncskew_t$	(4) $Ncskew_t$
$Fluidity_{t-1}$	0.091***	0.099***	0.232***	0.230***
	[0.019]	[0.019]	[0.042]	[0.041]
$Share_{t-1}$	0.015		0.054*	
	[0.013]		[0.027]	
$Fluidity_{t-1} \times Share_{t-1}$	-0.068**		-0.168***	
	[0.028]		[0.059]	
$Tnic_{t-1}$		0.034***		0.063**
		[0.013]		[0.026]
$Fluidity_{t-1} \times Tnic_{t-1}$		-0.073**		-0.164***
		[0.028]		[0.059]
$Controls_{t-1}$	Yes	Yes	Yes	Yes
Constant			-0.780***	-0.781***
			[0.045]	[0.047]
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
# Obs.	27,995	27,988	27,995	27,988
Pseudo / Adj. R^2	0.0276	0.0276	0.057	0.057

Panel B: Subsample Analysis by Financial Constraints

Variables	(1) $Crash_t$	(2) $Crash_t$	(3) $Crash_t$	(4) $Ncskew_t$	(5) $Ncskew_t$	(6) $Ncskew_t$
$Fluidity_{t-1}$	0.019	0.040**	0.071***	0.077*	0.097**	0.166***
	[0.020]	[0.020]	[0.017]	[0.042]	[0.042]	[0.038]
HP_{t-1}	-0.042***			-0.061**		
	[0.012]			[0.025]		
$Fluidity_{t-1} \times HP_{t-1}$	0.098***			0.172***		
	[0.025]			[0.054]		
WW_{t-1}		-0.026**			-0.054**	
		[0.013]			[0.027]	
$Fluidity_{t-1} \times WW_{t-1}$		0.050**			0.122**	
		[0.025]			[0.054]	
$Dividend_{t-1}$			0.005			-0.006
			[0.012]			[0.024]
$Fluidity_{t-1} \times Dividend_{t-1}$			-0.055*			-0.074
			[0.031]			[0.061]
$Controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Constant				-0.729***	-0.729***	-0.731***
				[0.047]	[0.050]	[0.045]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	27,963	27,798	27,971	27,963	27,988	27,971
Pseudo / Adj. R^2	0.0279	0.0276	0.0276	0.057	0.057	0.057

Panel C: Subsample Analysis by Information Asymmetry

Variables	(1) $Crash_t$	(2) $Crash_t$	(3) $Crash_t$	(4) $Ncskew_t$	(5) $Ncskew_t$	(6) $Ncskew_t$
$Fluidity_{t-1}$	0.040**	0.107***	0.099***	0.127***	0.301***	0.192***
	[0.019]	[0.020]	[0.019]	[0.044]	[0.044]	[0.042]
High Ret_vol_{t-1}	-0.018			0.008		
	[0.012]			[0.024]		
$Fluidity_{t-1}$* High Ret_vol_{t-1}	0.069***			0.143***		
	[0.025]			[0.055]		
$Large_{t-1}$		0.058***			0.211***	
		[0.012]			[0.024]	
$Fluidity_{t-1}$* $Large_{t-1}$		-0.068***			-0.161***	
		[0.024]			[0.052]	
Old_{t-1}			0.021*			0.001
			[0.011]			[0.024]
$Fluidity_{t-1}$* Old_{t-1}			-0.081***			-0.097*
			[0.025]			[0.054]
$Controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Constant				-0.520***	-0.472***	-0.736***
				[0.033]	[0.037]	[0.046]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	27,995	27,995	27,995	27,995	27,995	27,995
Pseudo / Adj. R^2	0.0273	0.0278	0.0279	0.056	0.054	0.057

Table 9
Long-Run Impact of Competitive Threats on Crash Risk

The table presents the impact of year t-1 competition on crash risk in years t, t+1, and t+2. For fair comparisons, all the regressions require that the sample has non-missing information on the year t, t+1, and t+2 crash risk. Variable definitions are in Appendix A. Standard errors adjusting for heteroskedasticity and within-firm clustering are in brackets. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Crash_t$	$Crash_{t+1}$	$Crash_{t+2}$	$Ncskew_t$	$Ncskew_{t+1}$	$Ncskew_{t+2}$
$Fluidity_{t-1}$	0.065***	0.048**	0.029	0.161***	0.110***	0.081**
	[0.018]	[0.019]	[0.019]	[0.039]	[0.040]	[0.040]
$Dturn_{t-1}$	0.095***	0.044	0.021	0.362***	0.037	0.061
	[0.028]	[0.029]	[0.028]	[0.058]	[0.060]	[0.060]
$Ncskew_{t-1}$	0.000	0.002	0.001	0.007	0.005	0.016**
	[0.004]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
$Sigma_{t-1}$	1.538***	1.291***	1.153***	5.598***	4.971***	4.446***
	[0.386]	[0.380]	[0.382]	[0.736]	[0.775]	[0.774]
Ret_{t-1}	0.196***	0.150***	0.115***	0.615***	0.519***	0.462***
	[0.042]	[0.040]	[0.040]	[0.076]	[0.080]	[0.082]
$Size_{t-1}$	0.012***	0.008***	0.008***	0.069***	0.056***	0.046***
	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]	[0.004]
MB_{t-1}	0.006***	0.002	0.002	0.035***	0.021***	0.013***
	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]	[0.004]
Lev_{t-1}	-0.078***	-0.066***	-0.045*	-0.343***	-0.252***	-0.167***
	[0.023]	[0.024]	[0.024]	[0.046]	[0.049]	[0.051]
Roa_{t-1}	0.168***	0.124***	0.085***	0.356***	0.271***	0.150***
	[0.023]	[0.023]	[0.022]	[0.044]	[0.046]	[0.049]
Constant				-0.701***	-0.364***	-0.600***
				[0.046]	[0.046]	[0.046]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	19,259	19,259	19,259	19,259	19,259	19,259
Pseudo / Adj R^2	0.0313	0.0218	0.0186	0.065	0.037	0.028

Appendix: Variable Definitions		
Variables Used in Regression Analysis		
	Variable Type	Definition
Ncskew	Main dependent variable	The negative skewness of firm-specific weekly returns over the year ending three months after fiscal year end. The firm-specific weekly return is $W_{i,t} = \ln(1 + \varepsilon_{i,t})$, with the residual $\varepsilon_{i,t}$ estimated from the expanded market model regression: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t-2} + \beta_{2i} r_{m,t-1} + \beta_{3i} r_{m,t} + \beta_{4i} r_{m,t+1} + \beta_{5i} r_{m,t+2} + \varepsilon_{it}$, where $r_{i,t}$is the return on stock i in week t, and $r_{m,t}$ is the return on the CRSP value weighted market index in week t. Ncskew for year s is then computed below: $Ncskew_{is} = -\frac{n(n-1)^{3/2} \sum W_{it}^3}{(n-1)(n-2)(\sum W_{it}^2)^{3/2}}$, where n is the number of observations on weekly returns during year s.
Crash	Main dependent variable	An indicator variable equaling one for a firm-year (the year ending 3 months after fiscal year end) that experiences one or more crash weeks. We define the crash week as the week in which the firm's weekly return $W_{i,t}$ is 3.2 standard deviations below the mean firm-specific weekly returns over the entire fiscal year for this firm. Following Kim, Li, and Zhang (2011a,b), 3.2 is chosen so that the crash events account for 0.07% of frequency in the normal distribution.
Fluidity	Main independent variable	The product market fluidity variable obtained from Hoberg-Phillips Data Library (http://alex2.umd.edu/industrydata/). Fluidity is a "cosine" similarity between a firm's products and the changes in the rivals' products and is scaled between 0 and 1. Larger fluidity indicates greater product market threats. Details are in Hoberg, Phillips, and Prabhala (2014).
r_Fluidity	Alternative independent variable	The decile rank of *Fluidity*. In each fiscal year, we obtain the decile rank of the sample firms based on their *Fluidity* levels and scale the ranks to be in the interval (0,1].
Pctcomp	Alternative independent variable	Number of occurrences of competition-related words per 1,000 total words in the 10-K. This variable is from Feng Li's website at http://webuser.bus.umich.edu/feng/.
r_comp	Alternative independent variable	The decile rank of *Pctcomp*, computed each year and scaled to be in (0,1].
Exrt	IV	Industry-level (three-digit SIC) foreign exchange rate (dollar amount of foreign currency in U.S. dollars), computed as the source-weighted average of real exchange rates across all exporting countries, divided by 1,000 (Xu, 2012). For example, if one U.S. dollar is worth 1.09 Canadian dollars, then we use 0.00109 in calculating *Exrt*. An increase in *Exrt* indicates depreciation in foreign currency. Raw exchange rate data come from the International Financial Statistics of the International Monetary Fund (IMF), and is converted into the real rate using the exchanging countries' consumer price indices obtained from the IMF. The weights are the share of each exporting country in the three-digit SIC industry in 1997. We choose 1997 as the base year as our sample begins in 1998. The weights are fixed over time because according to Xu (2012), most industries have stable import shares by country.

Tariff	IV	Industry-level tariff rate. This variable is the yearly average of ad valorem tariff rate, which is the duties collected by the U.S. customs divided by the free-on-board value of imports at three-digit SIC level.
Dturn	Control variable	Average monthly share turnover over the current fiscal year period minus average monthly share turnover over the previous fiscal year period. Monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.
Sigma	Control variable	Standard deviation of firm-specific weekly returns during the fiscal year.
Ret	Control variable	Average firm-specific weekly returns over the fiscal year period, times 100.
Size	Control variable	Log of a firm's total assets.
MB	Control variable	Market value of equity divided by book value of equity.
Lev	Control variable	Total debt divided by market value of assets.
Roa	Control variable	Income before extraordinary items divided by total assets.
Pos_num	Analysis on information withholding	We obtain managers' forecasts of quarterly EPS from First Call, and compare these forecasts with analyst consensus for the same period. We categorize managers' earnings forecasts as positive (negative) if managers' forecasts are higher (lower) than analyst consensus. Pos_num is defined as the number of managers' positive forecasts for the year.
Neg_num	Analysis on information withholding	Neg_num is defined as the number of managers' negative forecasts for the year. Managers' earnings forecasts are categorized as negative if managers' forecasts are lower than analyst consensus.
Neg_pct	Analysis on information withholding	Neg_pct is defined as the percent of managers' negative forecasts out of the total number of managers' earnings forecasts for the year. Managers' earnings forecasts are categorized as negative if managers' forecasts are lower than analyst consensus.
Fog	Analysis on information withholding	The Fog index of annual financial report. Fog is equal to 0.4×(words per sentence + percent of complex words), where complex words are words with three syllables or more. A higher Fog index indicates less readable financial report. This measure is developed by Li (2008) and available from Feng Li's website.
NegFlesch	Analysis on information withholding	The negative of the Flesch Reading Ease Index. The Flesch Reading Ease index is calculated as 206.835-(1.015×words per sentence)-(84.6×syllables per word). The higher the Flesch index, the easier the text is. This measure is available from Feng Li's website. See Li (2008) for details on the measure. We use the negative of the Flesch index so that a higher NegFlesch indicates lower readability.
Kincaid	Analysis on information withholding	The Kincaid index is calculated as (11.8×syllables per word) + (0.39×words per sentence) – 15.59. The higher the Kincaid index, the more difficult the text is. This measure is available from Feng Li's website. See Li (2008) for details on the measure.

Length	Analysis on information withholding	Log of the number of words in the annual report. This measure is developed by Li (2008) and available from Feng Li's website.
Market Share	Subsample analysis	Proportion of a firm's sales in the three-digit SIC industry.
TNIC3HHI	Subsample analysis	Herfindahl index based on text-based network industry classifications (TNIC), from Hoberg-Phillips Data Library (http://alex2.umd.edu/industrydata/). A higher TNIC3HHI indicates a greater concentration in the text-based network industry.
HP Index	Subsample analysis	Hadlock and Pierece (2010) financial constraint index. HP Index for firm i in fiscal year t is computed below: $HP_{i,t} = -0.737 \times Size_{i,t} - 0.043 \times Size_{i,t}^2 - 0.040 \times Age_{i,t}$, where *Size* is log(inflation-adjusted book assets) (capped at log($4.5 billion), and *Age* is the current year minus the first year that the firm has a non-missing stock price on Compustat (winsorized at 37 years). The cap of log($4.5 billion) and the winsorization of 37 years follow from footnote 2 in Hadlock and Pierece (2010). Higher HP index indicates more financial constraints.
WW Index	Subsample analysis	Whited and Wu (2006) financial constraint index. WW Index for firm i in fiscal year t is computed below: $WW_{i,t} = -0.091 \times \frac{CashFlow_{i,t}}{Asset_{i,t-1}} - 0.062 \times Dividend_{i,t} + 0.021 \times Leverage_{i,t} - 0.044 \times Log\left(AT_{i,t}\right) + 0.102 \times IndustrySalesGrowth_{i,t} - 0.035 \times FirmSalesGrowth_{i,t}$, where *CashFlow* is operating cash flows, *dividend* is an indicator that equals one if the firm pays cash dividends, *leverage* is the ratio of long term debt to total assets, *AT* is total assets, and *industry sales growth* is the average sales growth of all firms in the same 3-digit SIC industry. Higher WW index indicates more financial constraints.
Dividend	Subsample analysis	An indicator variable equal to 1 if the firm has a non-zero cash dividend in the year and zero otherwise.
Old	Subsample analysis	An indicator variable equal to 1 if the firm's age is greater than the sample median, and zero otherwise.
Large	Subsample analysis	An indicator variable equal to 1 if the firm is larger than the sample median, and zero otherwise.
High Ret_vol	Subsample analysis	An indicator variable equal to 1 if the firm's stock return volatility is higher than the sample median, and zero otherwise.
	Variables Used in Natural Experiment	
Ncskew_Dif	Main dependent variable	The difference between the average of *Ncskew* three years after the tariff reduction (Ncskew_Post) and the average of *Ncskew* three years before (Ncskew_Pre).
Crash_Dif	Main dependent variable	The difference between the proportion of crash years during the three years after the tariff reduction (Crash_Post) and that during the three years before (Crash_Pre).

lag_dturn	Matching variable	*Dturn* averaged over the three years before the tariff reduction.
lag_sigma	Matching variable	*Sigma* averaged over the three years before the tariff reduction.
lag_ret	Matching variable	*Ret* averaged over the three years before the tariff reduction.
lag_size	Matching variable	*Size* averaged over the three years before the tariff reduction.
lag_mb	Matching variable	*MB* averaged over the three years before the tariff reduction.
lag_lev	Matching variable	*Lev* averaged over the three years before the tariff reduction.
lag_roa	Matching variable	*Roa* averaged over the three years before the tariff reduction.
Ncskew_Pre	Matching variable	*Ncskew* averaged over the three years before the tariff reduction.
Cut #x	Event variable	An indicator equal to one if the reduction in the import tariff rate is at least x (x=1, 2, 3, 4, 5) times the median tariff reduction in the same three-digit SIC industry, and zero otherwise.